An Automatic Tuning Method of a Fuzzy Logic Controller for Nuclear Reactors

Pramath Ramaswamy, Robert M. Edwards, and Kwang Y. Lee

Abstract—**The design and evaluation by simulation of an automatically tuned fuzzy logic controller is presented. Typically, fuzzy logic controllers are designed based on an expert's knowledge of the process. However, this approach has its limitations in the fact that the controller is hard to optimize or tune to get the desired control action. A method to automate the tuning process using a simplified Kalman filter approach is presented for the fuzzy logic controller to track a suitable reference trajectory. Here, for purposes of illustration an optimal controller's response is used as a reference trajectory to determine automatically the rules for the fuzzy logic controller. To demonstrate the robustness of this design approach, a nonlinear six-delayed neutron group plant is controlled using a fuzzy logic controller that utilizes estimated reactor temperatures from a one-delayed neutron group observer. The fuzzy logic controller displayed good stability and performance robustness characteristics for a wide range of operation.**

I. Introduction

An observer-based optimal state feedback controller was developed to achieve improved temperature performance for a wide range of operating conditions through use of a relatively simple low order time-invariant controller [1]–[3]. The design of an observer and optimal controller is in general based on an assumed linear model that is an approximate representation of an otherwise nonlinear plant. Moreover, the controller takes precise measurements of plant variables and generates a precise control variable. As an alternative to this model-based controller design, this paper considers fuzzy logic, which neither relies on an accurate description of the plant, nor on the precise measurements. An introduction to the fundamental concepts of fuzzy logic has been given by Zadeh [4].

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Most existing fuzzy logic controllers are designed without the use of any mathematical model of the underlying process [5]. These controllers are generally based on an expert's understanding of the process. Improved performance of important process variables is not usually a priority when fuzzy logic controllers are developed in this manner. Another approach that has been considered is to design a controller based on the knowledge obtained of the system from repeated simulations conducted on a mathematical model [6]. In either case, the rule base of the fuzzy logic controller has to be fine-tuned or calibrated using trial and error in order to obtain the desired performance.

The development and application of a fuzzy logic controller for improving reactor temperature performance in a robust manner is presented, Fig. 1. A unique aspect of this controller is that it uses a simple low-order observer estimate of the reactor temperature as the primary feedback signal rather than the full state feedback signal. Furthermore, a method of automatically tuning this fuzzy logic controller's critical parameters to achieve a desirable reactor temperature response has also been developed. For illustration purpose an observer-based optimal state feedback controller is used as a possible reference model for the desired response. The unknown parameters in the fuzzy logic controller rule base are determined using the Kalman filter algorithm.

In earlier work [6], robustness was demonstrated by considering the effect of process and measurement noise for a model linearized about the full power operating point. In [5], observations on the effect of high frequency noise, and other considerations such as initial conditions, changing rod worth, and sensor failures are reported. Performance of the fuzzy logic controller is demonstrated for a wide range of reactor operations over the power range of 10–100% and with significant plant parameter variations. This demonstration is conducted by applying the fuzzy-logic controller with a temperature estimate based on a simple one-delayed neutron group to a higher order nonlinear plant simulation with six-delayed neutron groups.

Section II provides general information on the design of a fuzzy logic controller. The algorithm for automating the fine tuning of the fuzzy logic controller is discussed in

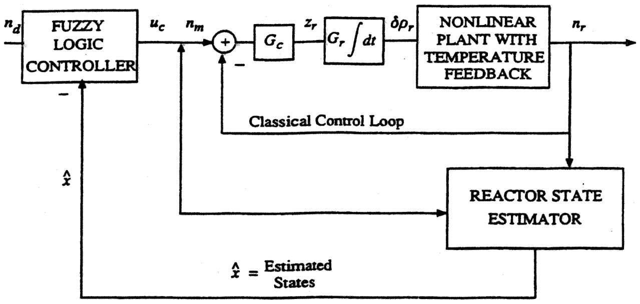

Fig. 1. Fuzzy logic controller using estimated temperature as feedback.

Section III. Section IV presents the fuzzy logic controller as designed for a nuclear reactor. The results that were obtained from the simulations are presented in Section V and conclusions are given in Section VI.

II. Fuzzy Logic Controller

In practice, it is not always easy to describe a system by means of a precise model so as to realize ideal optimal compensation. Thus, systems are usually controlled by other less capable control algorithms. Such systems cannot easily cope with a varying control environment or a system nonlinearity [7].

Model Reference Adaptive Control (MRAC) is an approach for coping with environmental variations and system nonlinearities. In this method, the controller's parameters are adjusted using suitable adaptive laws so that the system behaves like the reference model. The difficulty with this approach is the formulation of the input–output relationship by means of precise mathematical models. When such models are developed, they may be too computation-intensive for a real-time solution [7].

The fuzzy logic is, however, based on intuition and experience, and can be regarded as a set of heuristic decision rules or "rules of thumb." One of the most interesting applications of fuzzy logic [4] was the development of the fuzzy logic controller. A fuzzy logic controller is shown in Fig. 2, which consists of:

1) A rule base which contains a number of control rules.
2) A database which defines the membership functions of the linguistic terms used in the rule base.
3) An inference mechanism based on the control rules.
4) A fuzzification unit to map real inputs from sensors into the fuzzy terms.
5) A defuzzification unit to map fuzzy outputs of the inference mechanism to real numbers.

A fuzzy logic controller uses a set of control rules and an inference mechanism to determine the control action for a given process state, Fig. 2. The control rules are fuzzy expressions that relate the fuzzy process variables (controller inputs) to the fuzzy controller outputs. The inference mechanism evaluates the rule base to find the appropriate control action.

A. Rule Base

A fuzzy control action consists of situation and action pairs. Conditional rules expressed in IF and THEN statements are generally used. Here, the IF portion is the ANTECEDENT, and the THEN portion is the CONSEQUENT. There are generally two kinds of fuzzy rules that are used in fuzzy logic controllers:

1) rules whose consequents are fuzzy sets,
2) rules whose consequents are parameterized functions.

The First Type: To illustrate the two cases consider a fuzzy controller based on a rule base as follows:

$$\text{IF } x_1 \text{ is } A_1, x_2 \text{ is } A_2, \qquad \text{THEN } u \text{ is } B_1, \tag{1}$$

where x_1 and x_2 are process variables (inputs to the controller) such as "error," and "change in error" respectively, and u is the "input to the plant." Here A_1, A_2, and B_1 are fuzzy sets defined on the input space (of x_1 and x_2) and output space (of u), respectively. This rule may be further simplified by reducing the consequent B_1 to a fuzzy singleton

$$\text{IF } x_1 \text{ is } A_1, x_2 \text{ is } A_2, \qquad \text{THEN } u \text{ is } 1.15. \tag{2}$$

This simple rule may be interpreted as "if the error is small negative and the change in error is large negative, then the input to the plant is 1.15." Although in this example x_1 and x_2 are connected by logical and for simplicity, the logical or may also be used in conjunction with the logical and.

The Second Type: In this approach proposed by Takagi and Sugeno [7], the fuzzy controller consists of a number of rules which are written as:

$$\text{IF } f(x_1 \text{ is } A_1, \cdots, x_k \text{ is } A_k), \qquad \text{THEN } y = g(x_1, \cdots, x_k), \tag{3}$$

where

- y variable of the consequent whose value is inferred.
- x_i variables of the premise that also appear in the consequent.
- A_i fuzzy sets with linear membership functions representing a fuzzy subspace in which the above IF-THEN rule can be applied.
- f logical functions connecting the propositions in the premise.
- g function that implies the value of y when $x_1, \cdots, x_k$ satisfy the premise.

The consequent (the outputs, or drive) used in this method are parameterized functions of the input variables. To apply rules like this to fuzzy algorithms for process control, the variables of the premise and the consequent are defined as the following:

Error (E) = process output − set point
Error change (DE) = current error − last error
Controller output = input applied to process.

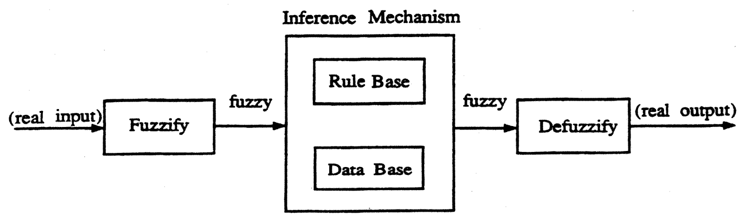

Fig. 2. Internal structure of a fuzzy logic controller.

The domain of a variable, E or DE, is partitioned into fuzzy sets, A_i, $i = 1, 2 \cdots$. Every fuzzy set A_i is associated with a name that represents qualitative statements, e.g., for $i = 1, 2, \cdots, 5$, A_1 = large negative (LN), A_2 = small negative (SN), A_3 = zero (ZE), A_4 = small positive (SP), and A_5 = large positive (LP). In general i is not limited to 5. In a rule base of the second type, where the consequent of a rule is a parameterized function of the input variables, f_{ij} is an abbreviation of $f(x_1$ is A_i, x_2 is $A_j)$, for all possible i, j. An example of a rule from this rule base is

IF error (E) is large negative ($i = 1$) and the change in error (DE) is small negative ($j = 2$),

then the *output* is

$$f_{12} = u_{12} = c_{12}^0 + c_{12}^1 E + c_{12}^2 DE, \quad (4)$$

where the subscripts represent $Rule_{12}$.

B. Membership Functions

In the area of control, the definition of membership functions follows two different approaches: Either 1) one defines the functions and identifies the system parameters, or 2) one works with a given system and identifies the membership function under the controlled process [9]. In this work method 1) is followed.

Generally, there is no restriction on the shape of a membership function. However, triangular, bell-shaped, or the monotonic linear functions, are usually adopted in the formulation of the membership function.

Several functions exist in the literature for generalized membership functions. Recently, a new class of membership function has been proposed by Dombi [9]. This function can be described with only four parameters, and they are easy to determine. The first two define the interval $[a, b]$, λ is the sharpness, and ν determines the inflection point of the S-shaped functions. The resulting membership functions consist of the monotonically increasing function

$$\mu(x) = \frac{(1-\nu)^{\lambda-1}(x-a)^{\lambda}}{(1-\nu)^{\lambda-1}(x-a)^{\lambda} + \nu^{\lambda-1}(b-x)^{\lambda}}, \quad x \in [a, b], \quad (5a)$$

and the monotonically decreasing function

$$\mu(x) = \frac{(1-\nu)^{\lambda-1}(b-x)^{\lambda}}{(1-\nu)^{\lambda-1}(b-x)^{\lambda} + \nu^{\lambda-1}(x-a)^{\lambda}}, \quad x \in [a, b]. \quad (5b)$$

If $\lambda = 1$, then the two equations reduce to the linear form. The linear form will be used throughout this discussion, Fig. 3.

Membership functions are generally chosen to be sufficiently wide and to reduce sensitivity to noise. Therefore the choice of the membership function may also play a role in the robustness of the controller [10].

C. Fuzzification

The strategy that has been most commonly used in control applications is that in fuzzification a measured value is converted into a fuzzy *singleton* within a universe of discourse. In this method, the measurement x_0 is interpreted as belonging to a fuzzy set A with a membership function $\mu(x)$, where $\mu(x_0) = 1$. This simplified approach is also used in this work.

D. Defuzzification

Defuzzification is mapping the space of fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy control actions. The defuzzifier is essential because most real processes that require control need real inputs. Several strategies exist at present: the mean of the maximum, the centroid of area, and the fuzzy mean. Each approach has its advantages [11]. In this work, the defuzzification strategy that is used to form the output (u_c) of the fuzzy logic controller is the weighted average of the individual rule outputs u_{ij}. This is most convenient when using rules of the second type, i.e., the output of each rule is a parameterized function of inputs as shown in (4).

The μ_{ij} attached to each u_{ij} is the weight attached to each rule ij; and

$$\mu_{ij} = \mu_{A_i}(E) \wedge \mu_{A_j}(DE), \quad (6)$$

or

$$\mu_{ij} = \mu_{A_i}(E) \times \mu_{A_j}(DE), \quad (7)$$

where A_i, A_j are generic terms for the fuzzy linguistic sets or qualitative statements like large negative (LN) defined for E and DE. The multiplicative weights ($\times$) are

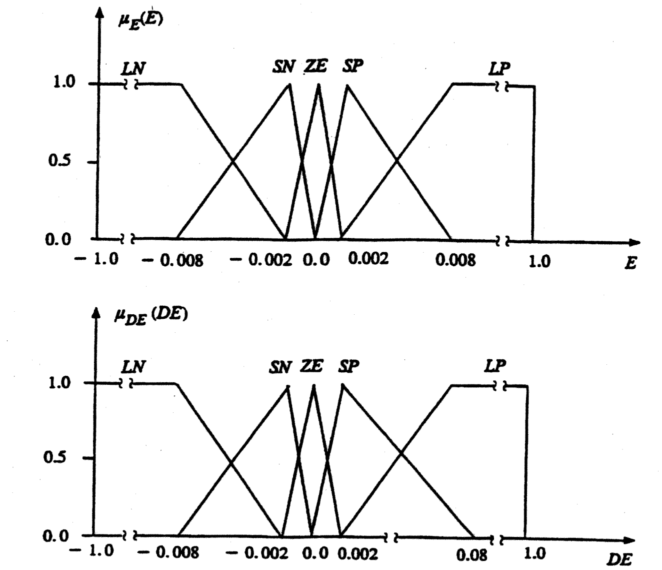

Fig. 3. Membership functions for error (E) and change in error (DE).

preferred over the *min* ($\wedge$) because of their smoothness properties.

The output of the controller is therefore:

$$u_c = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_{ij} u_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_{ij}}. \tag{8}$$

III. An Automatic Tuning Method for the Fuzzy Logic Controller

Most existing fuzzy logic controllers are designed without using any mathematical model of the underlying process. The construction procedures are generally based on the experts' understanding of the process and do not involve any detailed mathematical descriptions. Therefore, the rule base of a fuzzy logic controller must be adjusted through trial and error to obtain the desired performance.

In this section, an automatic tuning method (ATM) for the fuzzy logic controller is presented. In the proposed method, the fuzzy logic controller uses parameterized output functions as the consequents to rules. These parameters permit the use of numerical algorithms to modify the output of the controller. In this approach, phase-space based information about the system's global behavior is used to determine the controller output function parameters [12]. Input–output data (input to controller, actual controller output, and the desired controller output) are used to fine tune the controller by estimating the parameters of the consequents of the rules through an application of the Kalman filter algorithm.

Recall from (4) that the control action for any $Rule_{ij}$, consists of an if situation then action pair. IF error (E) is A_i and the change in error (DE) is A_j, THEN the output is of the form:

$$f_{ij} = u_{ij} = c_{ij}^0 + c_{ij}^1 E + c_{ij}^2 DE. \tag{9}$$

The consequent here is $f_{ij}(E, DE)$ and the constants c_{ij}^l, $l = 0, 1, 2$, are the parameters to be modified to optimize or to calibrate the fuzzy logic controller.

In general, each control rule determines a particular control law $f_{ij}(\cdot)$ for the region of space delimited by the antecedent's fuzzy sets. For the $f_{ij}(\cdot)$ as defined above, i.e., $f_{ij}(E, DE)$ where E is the process error, and DE is the change in error, the controller can be viewed as a proportional-derivative (P–D) controller with an offset [12]. However, unlike the classical P–D controller, the fuzzy logic controller utilizes a number of P–D controllers simultaneously as a weighted average defined by equation (8).

A. Output Function Parameter Modification

The if part of the fuzzy logic controller defines the phase-space over which the rule operates. The then part of the rule defines the control action to be taken by the controller in that region. Once a rule base is specified, the modification of the output or the consequent functions of the control rules is done through setting the parameters c_{ij}^l based on the input–output data. Each element of the input–output data set consists of actual inputs to the controller ($E(k)$, $DE(k)$), the actual outputs of each $Rule_{ij}$ of the controller ($u_{ij}(k)$), and the desired output of the controller ($d(k)$, where k is the discrete-time element of the input–output data set). To fine tune the controller so that it meets the desired control policy, the c_{ij}^l are identified from the non-zero measures $\mu_{A_i}(E(k))$ and $\mu_{A_j}(DE(k))$ of the error and the change in error for the process and they are adjusted to minimize the mean-squared error between the actual and a desired output $d(k)$, such as a reference model output. The algorithm approximates the parameters c_{ij}^l that minimize the mean-square error (MSE) of the output of the controller with respect to the desired output $d(k)$. For this purpose the following automatic tuning method (ATM) is considered using the Kalman filtering.

B. Automatic Tuning Method

The consequent $u_{ij}(k)$ of each rule of the controller has the form $c_{ij}^0 + c_{ij}^1 E(k) + c_{ij}^2 DE(k)$. The offset c_{ij}^0 is known, and it is either the steady-state controller output or it is the desired output when the error and the change in error are zero. Thus, the resulting parametric equation simplifies to

$$u_{ij}(k) = c^0 + c_{ij}^1 E(k) + c_{ij}^2 DE(k), \tag{10}$$

where c_{ij}^1 and c_{ij}^2 are the only unknowns. To find these unknowns, the Kalman filter approach [13], which is a recursive filter algorithm, is taken because the Kalman filter estimates are the optimal mean-squared error estimates. Also, in a recursive filter there is no need to store past measurements for the purpose of computing present estimates. In order to apply the Kalman filtering, the unknown parameters c_{ij}^l are viewed as state variables, the premise variables $E(k)$ and $DE(k)$ as time-varying system coefficients, and the $u_{ij}(k)$ as the system output variables. Then, the dynamics of the c_{ij}^l can be modeled simply as a stochastic system in discrete-time:

System Model:

$$\begin{bmatrix} c_{ij}^1(k) \\ c_{ij}^2(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} c_{ij}^1(k-1) \\ c_{ij}^2(k-1) \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} w_{(k-1)}$$

$$w_k \sim N(0, \infty). \tag{11}$$

Measurement Model:

$$u_{ij} = [E(k) DE(k)] \begin{bmatrix} c_{ij}^1(k) \\ c_{ij}^2(k) \end{bmatrix} + v_k + c^0 \tag{12}$$

$$v_k \sim N(0,0), \qquad R_k^{-1} = \infty,$$

where w_k and v_k are process and measurement noise, respectively, with normal distribution. In this formulation, the process noise is assumed to be completely unknown and the measurement model is assumed to have zero measurement noise. The parameters are unknown constants and therefore their changes at steady-state are zero. Also, the variances of the two parameters are uncorrelated. From these initial assumptions for the system model, the Kalman filtering problem can be easily solved [13] to give the steady-state solution for the parameters c_{ij}^l.

IV. Fuzzy Logic Controller for Nuclear Reactor

The basic design approach is to place the fuzzy logic controller as the outermost controller as shown in Fig. 1. In this way, the embedded classical controller can be retained to facilitate incremental upgrades to existing plants. However the embedded classical controller is optional and the fuzzy logic controller can be designed with or without the embedded classical control loop.

The verification testing of the fuzzy logic controller is conducted via simulation where the simulated plant is a continuous-time model whose nonlinear equations are solved via numerical integration using the advanced continuous simulation language (ACSL) [14]. The fuzzy logic controller is simulated as a discrete or sampled-data controller which communicates with the simulated plant ten times per second.

A. Nuclear Reactor Model

To demonstrate the fuzzy logic controller configuration discussed in this paper, a simple simulation model of a pressurized water reactor (PWR) was used. The model assumes point kinetics with six delayed neutron groups and temperature feedback from lumped fuel and coolant temperature calculations which are summarized as follows [1]–[3]:

$$\frac{dn_r}{dt} = \frac{\delta\rho - \beta}{\Lambda} n_r + \frac{1}{\Lambda} \sum_{i=1}^{G} \beta_i c_{ri}, \tag{13a}$$

$$\frac{dc_{ri}}{dt} = \lambda_i n_r - \lambda_i c_{ri} \qquad i = 1 \cdots G, \tag{13b}$$

$$\frac{dT_f}{dt} = \frac{f_f P_0}{\mu_f} n_r - \frac{\Omega}{\mu_f} T_f + \frac{\Omega}{2\mu_f} T_l + \frac{\Omega}{2\mu_f} T_e, \tag{13c}$$

$$\frac{dT_l}{dt} = \frac{(1-f_f)P_0}{\mu_c} n_r + \frac{\Omega}{\mu_c} T_f - \frac{(2M+\Omega)}{2\mu_c} T_l + \frac{(2M-\Omega)}{2\mu_c} T_e, \tag{13d}$$

$$\frac{d\delta\rho_r}{dt} = G_r Z_r, \tag{13e}$$

$$\delta\rho = \delta\rho_r + \alpha_f (T_f - T_{f0}) + \frac{\alpha_c (T_l - T_{l0})}{2} + \frac{\alpha_c (T_e - T_{e0})}{2}. \tag{13f}$$

The model (13) represents a nonlinear system. The model is nonlinear because reactivity $\delta\rho$ multiplies the relative reactor power state variable n_r as seen in (13a). Reactivity includes the control rod reactivity state $\delta\rho_r$ and the feedback from the reactor temperature states. Also μ_c, Ω, M, α_f, and α_c are not constants but rather a function of the equilibrium power level n_{r0}. Equation (14) shows the dependence of these variables on n_{r0} [15]:

$$\mu_c(n_{r0}) = \left(\frac{160}{9} n_{r0} + 54.022\right) MWs/°C \tag{14a}$$

$$\Omega(n_{r0}) = \left(\frac{5}{3} n_{r0} + 4.9333\right) MW/°C \tag{14b}$$

$$M(n_{r0}) = (28.0 n_{r0} + 74.0)\ MW/°C \tag{14c}$$

$$\alpha_f(n_{r0}) = (n_{r0} - 4.24) \times 10^{-5} \frac{\delta k}{k} /°C \tag{14d}$$

$$\alpha_c(n_{r0}) = (-4.0 n_{r0} - 17.3) \times 10^{-5} \frac{\delta k}{k} /°C, \tag{14e}$$

where n_{r0} is the equilibrium power level at $t = 0$.

B. Fuzzy Logic Controller

The state estimator provides temperature feedback to the fuzzy logic controller which is designed to improve reactor temperature performance in a manner similar to a dynamical model-based controller such as an observer-based, state-feedback-assisted controller [1]–[3], or an LQG/LTR robust controller [16].

The power demand signal n_d is converted to an exit temperature demand (T_d) signal by using the steady-state version of (13):

$$T_d = \frac{P_0 n_d}{M} + T_e. \tag{15}$$

The normalized error $E(k)$ is then:

$$E(k) = \left(\hat{T}_l(k) - T_d\right)/T_d, \qquad \text{if } T_d > \hat{T}_l(0) \tag{16a}$$

$$E(k) = \left(T_d - \hat{T}_l(k)\right)/\hat{T}_l(0), \qquad \text{if } T_d < \hat{T}_l(0), \tag{16b}$$

where $\hat{T}_l$ is the observer estimate of the exit temperature T_l. The change in error $DE(k)$ is

$$DE(k) = E(k) - E(k-1). \tag{17}$$

The desired output c^0 is equal to the external power demand signal. Therefore, the fuzzy controller rule base becomes:

$$u_{ij} = n_d + c_{ij}^1 E(k) + c_{ij}^2 DE(k).$$

C. Reference Model

The reference model for tuning and evaluating the performance of the fuzzy logic controller is designed based on an observer-based state-feedback-assisted controller [1]–[3]. The observer-based state-feedback-assisted controller is based on one-delay neutron group parameters ($G = 1$, $\beta = 0.006019$, $\lambda = 0.150$) and applied to the six-delayed neutron group ($G = 6$) reactor simulation listed in Table I. The time-invariant state feedback gain which achieves an improved reactor temperature response was taken from [17]. This reference model is chosen for illustration purpose to demonstrate the automatic tuning method (ATM). However, any reference model can be selected to generate desired response and provide data for the ATM.

D. Tuning of Fuzzy Logic Controller

To estimate the unknown parameters for the consequent of each rule, the fuzzy logic controller and the ATM were simulated in parallel with the reference model. The non-zero measures of the membership functions of the fuzzy logic controller (Fig. 3) were used to identify the rules that were applicable at any given instant. The reference model provided the desired output $d(k) = n_r(k)$ at that instant, and the ATM provided estimates of the unknown parameters, c_{ij}^1 and c_{ij}^2.

To start the ATM procedure, the plant initial condition of the unknown parameters were assumed to be equal to zero. The simulation was performed for $\pm 10\%$ step changes in the input demand signal (n_d). Simulations were carried out for several cases of initial conditions and for several different values of controller sampling intervals.

V. Results and Discussion

An observer-based state feedback optimal controller [1]–[3] was previously designed to achieve improved temperature performance for a wide range of operating conditions using a relatively simple low order time-invariant controller. The design objective of the fuzzy logic controller was to similarly achieve improved wide-range temperature performance. This section presents the evaluation of a fuzzy logic controller to meet this goal.

TABLE I
Reactor Model Parameters

Parameters	Values	Parameters	Values
λ_1	3.15	β_1	0.0002940
λ_2	1.19	β_2	0.0008049
λ_3	0.3125	β_3	0.002765
λ_4	0.1165	β_4	0.0011405
λ_5	0.0317	β_5	0.001257
λ_6	0.0127	β_6	0.0001745
Λ	2.0×10^{-5}	μ_f	26.3
P_0	2500	T_{e0}	290
f_f	0.92		

For the purpose of tuning and testing the fuzzy logic controller, the operation of the reactor was divided into nine regions based on the percent rod worth (of the nominal value 0.0145 = 100%) and the full power range as illustrated in Fig. 4. The robust optimal controller designed at full power with nominal plant parameters (Region 6) was used to generate the reference model response [1], [3]. The parameters (c_{ij}^1, c_{ij}^2) in the rule base of the fuzzy logic controller were estimated (tuned) using the reference model response to transients in Region 6.

The transients in these regions that were used for tuning the fuzzy logic controller consisted of $\pm 10\%$ step changes in power demand from the nominal 100% power. The parameters estimated by the ATM are summarized in Table II. To evaluate the performance of the resulting controller, it was then subjected to the following four groups of tests:

Case A: *Local Control*

1. 100% → 90% → 100% power level change in Region 6.

Case B: *Global Operation*

1. 40% → 50% → 40% power level change in Region 1.
2. 20% → 10% → 20% power level change in Region 2.

Case C: *Emergency Operation*

1. 100% → 25% huge step down from Region 5 to Region 3.

Case D: *Shut-down/Start-up*

1. 100% → 10% ramp down from Region 5 to Region 3, followed by a 10% → 100% ramp up with 15% per minute rate.

The tests above were conducted using the reactor model described in Section IV. The observer gains, rod worths, and fuzzy controller parameters were kept fixed at the values for which the controller was tuned, (i.e., in Region 6) while conducting these tests. In each case the performance of the fuzzy controller is compared with the performance of the optimal controller designed for the same reactor model [2]. The optimal controller's observer and feedback gains were also kept fixed at the values

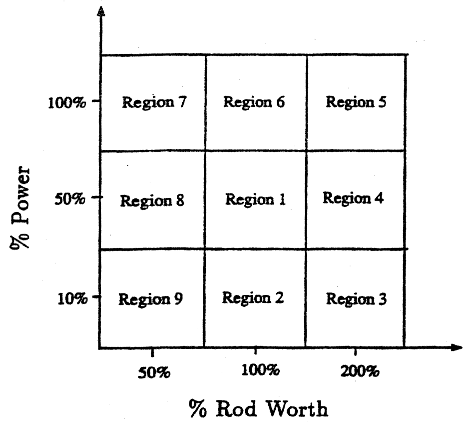

Fig. 4. The nine regions of reactor operation.

TABLE II
ESTIMATED PARAMETERS FOR RULE$_{ij}$

i	j	c_{ij}^1	c_{ij}^2
1	1	−14.15933	−13.54221
1	2	−8.544655	−24.15133
1	3	−6.055618	−26.03189
1	4	0.0000000	0.0000000
1	5	−0.2768038	0.5536076
2	1	−17.31362	−11.79659
2	2	−8.087297	−23.53640
2	3	−4.705722	−24.54666
2	4	0.0000000	0.0000000
2	5	−0.2768038	0.5536076
3	1	0.0000000	0.0000000
3	2	−15.16420	−13.17804
3	3	−15.16420	−13.17804
3	4	0.0000000	0.0000000
3	5	0.0000000	0.0000000
4	1	−16.14068	0.3889777
4	2	−34.63131	−19.88403
4	3	−6.911923	6.517233
4	4	0.0000000	0.0000000
4	5	0.0277524	0.5550497
5	1	−16.14068	0.3889777
5	2	−35.12094	−20.36247
5	3	−5.204771	4.770062
5	4	0.0000000	0.0000000
5	5	−0.0275841	−0.5516833

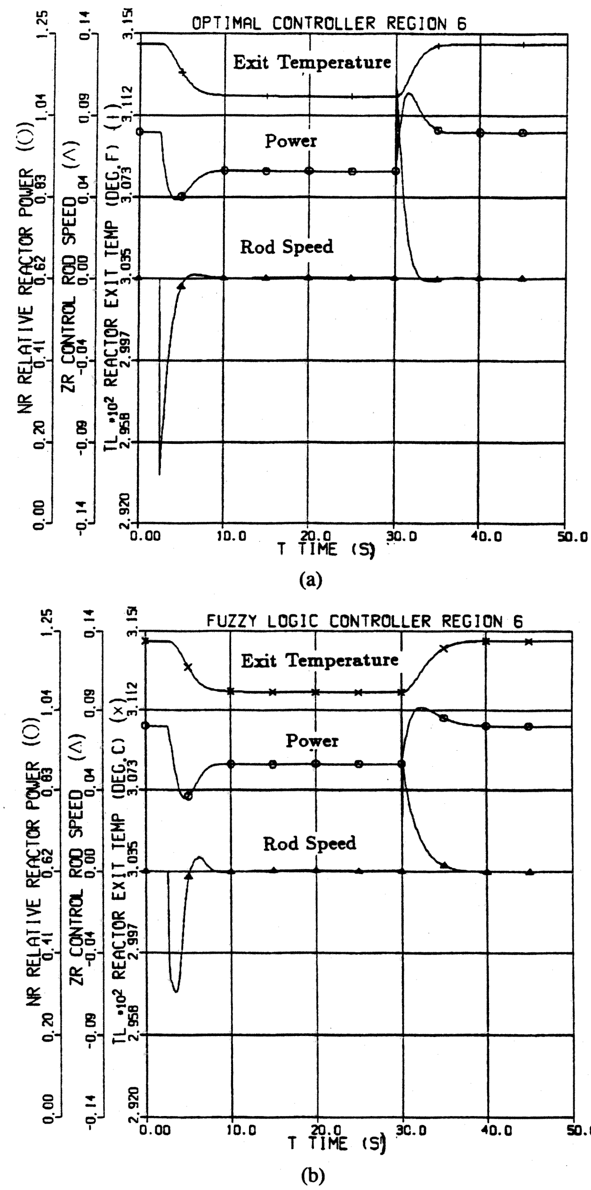

Fig. 5. Case A: Local control 100% → 90% → 100% power level change in region 6. (a) Optimal controller. (b) Fuzzy logic controller.

designed for Region 6 because these were considered to give the best overall performance when the controller was applied in other regions [3].

A. Local Control

Fig. 5 compares the optimal controller and the fuzzy logic controller responses near their design point (Region 6) for a 100% → 90% → 100% power level demand transient. The plots show the reactor exit temperature, reactor power output, and the control rod speed.

From Fig. 5(a) and (b) it is evident that the fuzzy logic controller performs as well as the optimal controller. The desired temperature is reached quickly and with no overshoot. For the comparable performance, the fuzzy logic controller shows smoother control rod speed compared with the optimal controller response. It should be noted that the fuzzy logic controller uses only the temperature estimate, while the optimal controller uses full state feedback.

B. Global Operation

Figs. 6 and 7 illustrate the robustness characteristics to parameter uncertainty resulting from global operation. Both the fuzzy logic controller tuned in Region 6 and the optimal controller designed for Region 6 are tested in other regions to see the applicability for global operation.

From the results of these experiments, it is evident that the fuzzy logic controller performs as well as the optimal controller in all regions. Both the optimal and the fuzzy controller perform best in the high power region (Fig. 5) as compared to the low power region (Fig. 7). Although not shown here, regions with higher percent rod worth showed comparable responses with faster temperature responses. Again, in this case the fuzzy logic controller

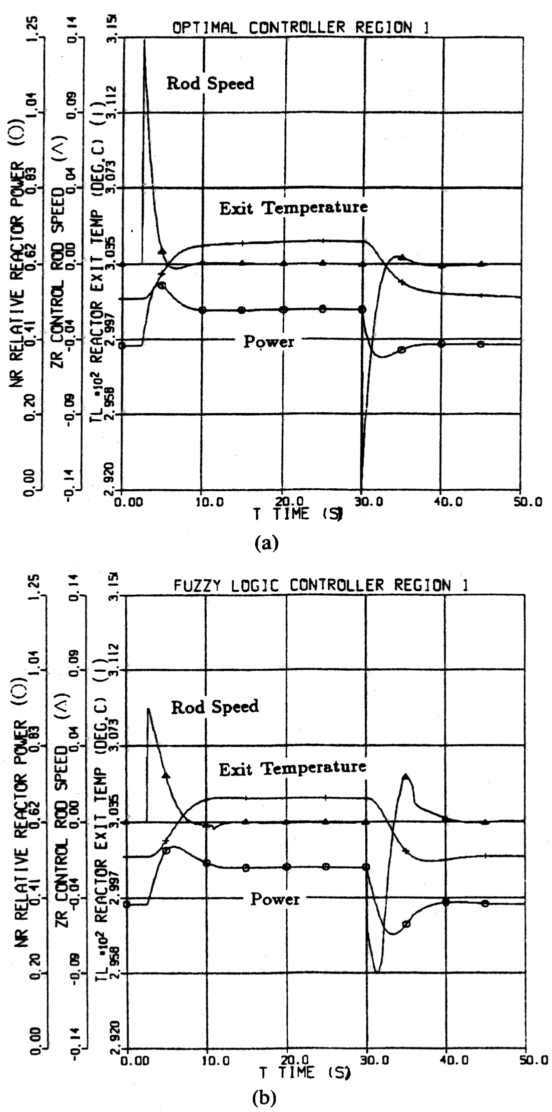

Fig. 6. Case B1: Global operation 40% → 50% → 40% power level change in region 1. (a) Optimal controller. (b) Fuzzy logic controller.

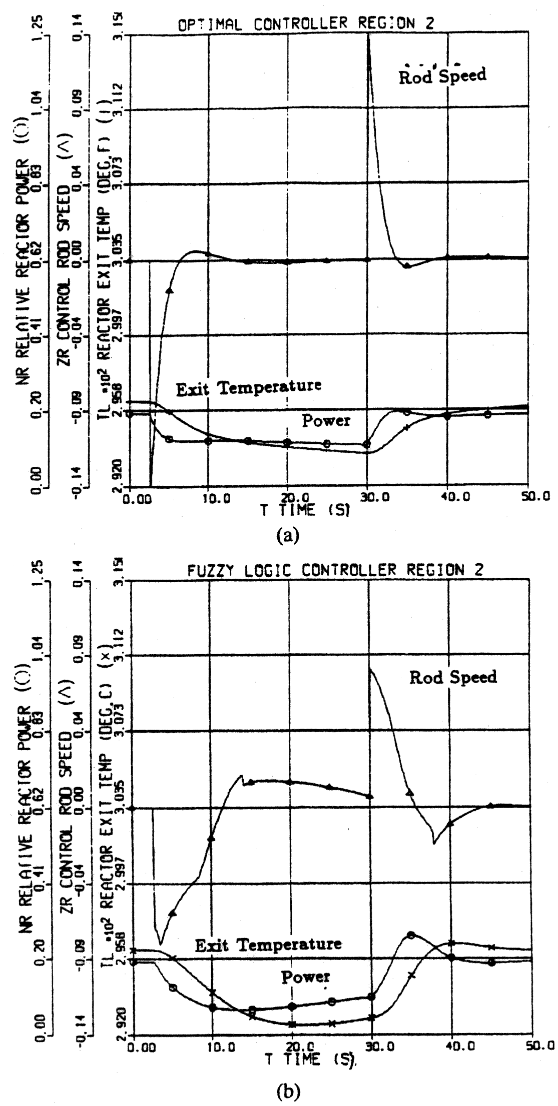

Fig. 7. Case B2: Global operation for 20% → 10% → 20% power level change in region 2. (a) Optimal controller. (b) Fuzzy logic controller.

showed smoother control rod speed compared to the optimal controller response.

C. Emergency Operation

This case represents the most stressed operation. In this test the system was operating in Region 5 (full power of 100%, and the rod worth of 0.0290 = 200% of the nominal value), and the input demand signal to the system is a large step change from 100% → 25%. The performance of the fuzzy logic controller is compared to the performance of the optimal controller which is illustrated in Fig. 8.

The fuzzy logic controller reaches the desired steady-state value of the temperature much faster than does the optimal controller. However, the fuzzy logic controller causes a noticeable overshoot. The reactor power and the control rod speed also show more overshoot. This is partly because the fuzzy logic controller uses only temperature feedback, while the optimal controller uses full state feedback. The advantage of the fuzzy logic controller in handling nonlinearities is not fully demonstrated in this case since it is not tuned over a wide range of operating conditions.

D. Shut-down / Start-up

This case mimics the beginning of shut-down/the end of start-up operation with a relatively fast ramp, 15% per minute. In this test the system is operating in Region 5 (full power of 100%, the rod worth of 0.0290 = 200% of the nominal value), and the input demand signal to the system is a fast ramp from 100% → 10% → 100%. The performance of the fuzzy logic controller is compared with the optimal controller's in Fig. 9.

The difference in the performance of the fuzzy logic controller and the optimal controller is not very distinct, except at certain transition points in the input demand signal. These transition points are located at the 30, 390, 510, and 870 second marks. While the difference is nil at

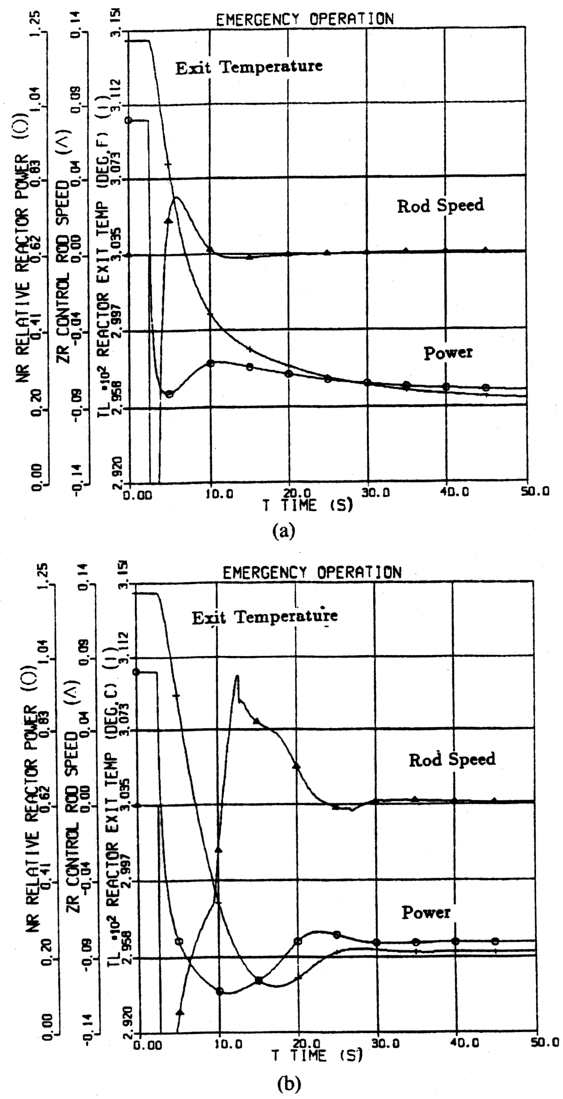

Fig. 8. Case C: Emergency operation 100% → 25% power level change in region 5. (a) Optimal controller. (b) Fuzzy logic controller.

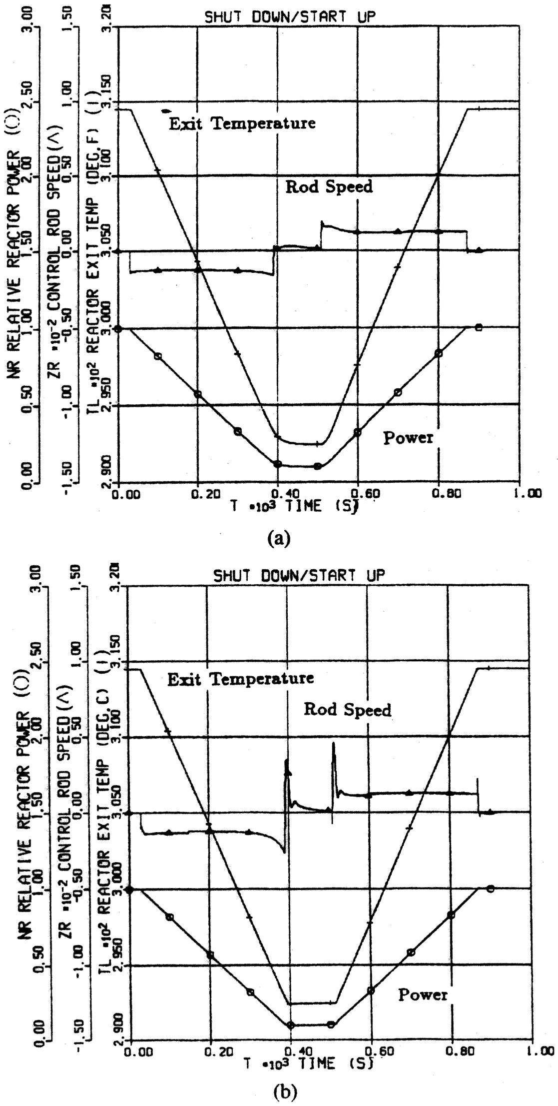

Fig. 9. Case D: Start-up/shut-down from region 5 for 100% → 10% → 100% power level change with 15% ramp. (a) Optimal controller. (b) Fuzzy logic controller.

the 30, and 870 second marks, there is noticeable difference at the 390 and 510 s marks. This difference is in the rod speed z_r for the fuzzy logic controller, which is higher than that of the optimal controller. In this case, however, the system with the fuzzy controller tracks the input demand signal much more closely throughout these transition points than the system with the optimal controller.

E. Summary of Evaluation Tests

In the simulation evaluation, the fuzzy logic controller is applied to higher order non-linear simulation of the reactor modeled with six delayed neutron groups and compared with the optimal controller responses. In all cases the fuzzy logic controller demonstrates good robustness for the range of uncertainties considered: 1) power level variations of a factor of ten, 2) control rod worth variation of a factor of four, 3) application to a high order plant (6 delayed neutron groups), and 4) application to a nonlinear plant. As indicated in Fig. 5(b), the fuzzy logic controller also achieves its best performance at its design power of 100%. At low power, far from the design point of 100% power, the optimal controller's improved temperature response is not as dramatic. The fuzzy logic controller on the other hand, accomplishes a faster temperature response at low power but with some noticeable temperature overshoots.

The optimal controller's acceptable performance and stability robustness over the power range of 10 to 100% with expected plant parameter variations have also been reported [2]–[3]. Although it maintains good stability robustness over the complete power range, improved temperature performance is not as dramatic if the operation is far from the design condition (e.g., at 10% power). Because reactor fuel temperatures are closer to their design limits at full power, it is considered more important for a controller to maintain tighter control of the reactor temperature at the full power condition. Hence, the design of a time-invariant fuzzy logic controller with desirable stability and performance robustness has been found to be best conducted at the 100% power and nominal plant parameters (Region 6).

Fuzzy logic originally developed by Zadeh [4] is to allow the processing of linguistic variables by machines. The technique is very useful for nonlinear systems because a linguistic rule can allow for a non-linearity whereas a linearized model-based controller cannot. This advantage, however, is not fully demonstrated. To reflect the nonlinearity caused by different operating points, the rule base needs to be expanded to include operating points in terms of power level and the control rod worth. This will increase the number of rules considerably (from twenty five for one region to two hundred and twenty five rules for all nine regions).

Since the primary objective of this paper is to demonstrate the automatic tuning method, the fuzzy logic controller is tuned only for Region 6, which is the full power and average control rod worth. The fuzzy logic controller designed this way, however, shows the robustness property when it is applied to all other regions and its performance is comparable with the optimal controller responses. Since the fuzzy logic controller is tuned at its design power, it works best at the full power. However, when a more general rule base is used by including different operating regions, the fuzzy logic controller would function better at all power levels.

The fuzzy logic controller performs just as well as the optimal controller inspite of the fact that the fuzzy logic controller uses only the temperature estimate for feedback, while the optimal controller uses full state feedback. Another interesting point to note is that a rule whose consequent is (10), may be viewed as a classical proportional-derivative (P–D) controller with an offset. However, the output of a fuzzy logic controller utilizing rules like these in its rule base, may be viewed as the weighted average of twenty five P–D controllers as shown in (9).

VI. Conclusions

The design and evaluation of an automatically-tuned fuzzy logic controller for improving reactor temperature performance in a robust manner has been detailed. The unique aspect of this controller is that it uses an observer estimate of the reactor temperature as the primary feedback signal rather than the full state feedback. Furthermore, a simplified method for automatically tuning the fuzzy logic controller's critical parameters to achieve desirable reactor temperature response, has also been presented. The robust performance of the fuzzy logic controller was demonstrated for a wide range of reactor operations, over the power range of 10–100% and with significant plant parameter variations.

The fuzzy logic controller robustness is comparable to a model-based state-feedback optimal controller when the plant output is assumed measured with certainty. However, the true efficacy of the fuzzy logic controller is probably for the case when there is considerable uncertainty in the plant output due to sensor failure or extreme plant uncertainty (severe faults). In this case, the fuzzy and/or neural network description and control of the process may be better suited than the utilization of model-based controller operating on assumed precise plant outputs [18].

References

[1] R. M. Edwards, K. Y. Lee, and M. A. Schultz, "Optimal control of reactor temperatures using reactivity," *Trans. Am. Nucl. Soc.*, vol. 61, pp. 287–288, 1990.

[2] R. M. Edwards, K. Y. Lee, and M. A. Schultz, "State feedback assisted classical control: An incremental approach to control modernization of existing and future nuclear reactors and power plants," *Nucl. Technol.*, vol. 92, Nov., pp. 167–185, 1990.

[3] R. M. Edwards, K. Y. Lee, and A. Ray, "Robust optimal control of nuclear reactors and power plants," *Nucl. Technol.*, vol. 98, May, pp. 137–148, 1992.

[4] L. A. Zadeh, "Outline of a New Approach to the Analysis of Complex Systems and Decision Processes," *IEEE Trans. Syst, Man, and Cyber.*, vol. SMC-3, no. 1, pp. 28–43, 1973.

[5] J. A. Bernard, "Use of a rule-based system for process control," *IEEE Con. Syst. Mag.*, vol. 8, no. 5, pp. 3–13, Oct. 1988.

[6] H. L. Akin and V. Altin, "Rule-based fuzzy logic controller for a PWR-Type nuclear power plant," *IEEE Trans. Nucl. Sci.*, vol. 38, no. 2, Apr. 1991.

[7] Y. F. Li and C. C. Lau, "Development of fuzzy algorithms for servo system," *IEEE Con. Syst. Mag.*, vol. 9, pp. 65–72, Apr. 1989.

[8] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its application to modeling and control," *IEEE Trans. Syst., Man, Cyber.*, vol. SMC-15, no. 1, pp. 116–132, Jan./Feb. 1985.

[9] J. Dombi, "Membership function as an evaluation," *Fuzzy Sets and Systems*, vol. 35, pp. 1–21, 1990.

[10] C. C. Lee, "Fuzzy logic in control systems: Fuzzy logic controller-Part 1," *IEEE Trans. Syst. Man, Cyber.*, vol. 20, no. 2, pp. 404–418, Mar./Apr. 1990.

[11] R. Zhao and R. Govind, "Defuzzification of fuzzy intervals," *Fuzzy Sets Syst.*, vol. 43, pp. 45–55, 1991.

[12] S. M. Smith and D. J. Comer, "Automated calibration of a fuzzy logic controller using a cell state space algorithm," *IEEE Contr. Syst. Mag.*, vol. 11, no. 5, pp. 18–28, Aug. 1991.

[13] A. Gelb, *Applied Optimal Estimation*, Boston: MIT Press, pp. 107–119, 1989.

[14] *Advanced Continuous Simulation Language (ACSL) Reference Manual*, Mitchell and Gauthier, Associates, Inc., Concord, MA, 1987.

[15] R. M. Edwards, "Robust optimal control of nuclear reactors and power plants," a Ph.D. Thesis in Nuclear Engineering, The Pennsylvania State University, May 1991.

[16] A. Ben-Abdennour, R. M. Edwards, and K. Y. Lee, "LQG/LTR Robust Control of Nuclear Reactor with Improved Temperature Performance," *IEEE Trans. Nucl. Sci.*, vol. 39, no. 6, pp. 2286–2299, Dec. 1992.

[17] R. M. Edwards, C. K. Weng, and R. W. Lindsay, "Experimental development of power reactor advanced controllers," in *The 8th Power Plant Dynamics, Control, and Testing Symposium*, Knoxville, TN, May 27–29, vol. 1, pp. 28.01–28.15, 1992.

[18] C. C. Ku, K. Y. Lee, and R. M. Edwards, "Improved Nuclear Reactor Temperature Control Using Diagonal Recurrent Neural Networks," *IEEE Trans. Nucl. Sci.*, vol. 39, no. 6, 1992.